TRB Paper No. 01-2887

Dynamic Freeway Travel Time Prediction Using Probe Vehicle Data: Link-based vs. Path-based

By

Mei Chen
Visiting Assistant Professor
National Center for Transportation and Industrial Productivity
New Jersey Institute of Technology
University Heights, Newark, NJ 07102-1982
Tel: (973) 596-5704
Fax: (973) 596-6454
Email: chenm@njit.edu

Steven I.J. Chien
Assistant Professor
Department of Civil and Environmental Engineering
New Jersey Institute of Technology
University Heights, Newark, NJ 07102-1982
Tel: (973) 596-6083
Fax: (973) 596-6454
Email: chien@njit.edu

Transportation Research Board
80th Annual Meeting
January 7-11, 2001
Washington, DC

Dynamic Freeway Travel Time Prediction Using Probe Vehicle Data: Link-based vs. Path-based

Mei Chen, National Center for Transportation and Industrial Productivity, NJIT, Newark, NJ 07102
Steven I. Chien, Department of Civil and Environmental Engineering, NJIT, Newark, NJ 07102

Abstract. Short-term travel time prediction is very important to the real time travelers' information and route guidance system. Various methodologies have been developed for dynamic travel time prediction. However, most of the existing studies presume that path travel time is the simple addition of travel times on the consisting links. Through simulation, it is shown that, under recurrent traffic condition, direct measuring of path based (or movement based) travel time rather than link based travel times could generate a more accurate prediction. Factors that would have an impact on the prediction accuracy are analyzed.

Keywords: Probe Vehicle, Data, Travel Time, Prediction

INTRODUCTION

With the development of the Advanced Travelers Information Systems (ATIS), short-term travel time prediction is becoming increasingly important. As a key input for the dynamic route guidance system, travel time information enables the generation of the shortest path (or alternative paths) connecting the origins (or current locations) and destinations.

There has been much research on the travel time prediction. In the context of prediction methodologies, various time series models (1, 2, 3) and artificial neural network models (4, 5) have been developed. In the context of input data source, most previous studies used "indirect" travel time data (1, 2, 6, 7, 8). That is, traffic data such as volume, occupancy, and speed were obtained directly, while travel time was calculated as a function of these parameters. Even though the general relation among these parameters has been explored widely, the specific coefficients in the function are most likely site specific. Moreover, this general relation might not stand during near-capacity flow condition.

While travel time data can be obtained through various sources, such as loop detectors, microwave detectors, radar, etc., it is unrealistic to hope that the whole roadway network is completely covered by such data collection devices. With the development of wireless communication technology, probe vehicles as "mobile detectors" are considered as a valuable source of real-time traffic data. There has been some research on the appropriate probe percentage as well as its report frequency to ensure reliable travel time estimation (10, 11, 12).

In most existing studies focused on link travel time estimation/prediction (3, 7, 9), it is generally assumed that path travel time is the addition of the travel times on its consisting links. However, for a probe-based data collection system in which the number of reports is rather limited, this link-based estimation/prediction might not be reliable. For example, for the intersection shown in Figure 1, if the probe (the marked vehicle) is on the left-turn lane which is experiencing serious backup, it might report a much longer travel time than the "true" average travel time on this link. Since the left-turn movement and through movement may experience a larger difference in their time to traverse the intersection, it makes more sense to measure the travel time based on path (a roadway segment consisting of multiple links) rather than link.

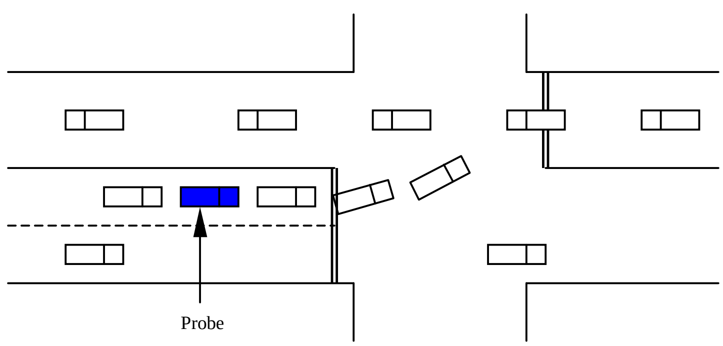

Figure 1 Vehicle Movement at Intersection

The purpose of this paper is to evaluate the performance of dynamic travel time prediction models with real-time data (travel time) collected by probe vehicles on path and its consisting link, respectively. We start in the next section by introducing the forecasting methodology that is used. Then, an example is presented to illustrate the data collection procedure and the performance of the forecasting models, followed by the results analysis and discussion.

PREDICTION METHODOLOGY

Travel time can be affected by various factors, such as volume, geometric conditions, speed limit, incidents, vehicle composition, etc. In real world applications, it is quite difficult to model the relation among all these factors, especially when traffic volume is near capacity (this could happen during the peak period of the day). Therefore, instead of using speed or volume data collected by conventional loop detectors and convert them into travel time information, we directly measure the travel times of vehicle probes for dynamically predicting travel time.

Various techniques have been used to predict travel time, as mentioned earlier. The Kalman filtering method (13) is chosen in the study because it enables the prediction of the state variable (in this study, travel time) to be continually updated as new observation (of travel time) becomes available. This approach has been used in the forecasting of traffic volume (14, 15) and real-time demand diversion (16), as well as the estimation of trip-distribution and traffic density (15). In this study, this technique is used to perform travel time prediction based on real-time information provided by probe vehicles. Specifically, the average travel time of probe vehicles at each time period is used as the real-time observation to predict the travel time in the next (or future) time period.

Let $x(t)$ denote the travel time at time interval t that is to be predicted, $\phi(t)$ denote the transition parameter at time interval t which is externally determined, and $w(t)$ denote a noise term that has a normal distribution with zero mean and a variance of $Q(t)$. The system model can be written as

$$x(t) = \phi(t-1)x(t-1) + w(t-1)$$

Let $z(t)$ denote the observation of travel time on time interval t and $v(t)$ denote the measurement error at time interval t that has a normal distribution with zero mean and a variance of $R(t)$. Since no traffic parameter other than travel time is involved, the observation equation associated with the state variable $x(t)$ is given by

$$z(t) = x(t) + v(t)$$

In our application, $z(t)$ is obtained from averaging the travel times reported by probe vehicles at time interval t. Historical data (e.g., travel time data from the same time period of a previous day with similar traffic situation) are used to obtain the transition parameter $\phi(t)$, which describes the relationship between the statuses of state variable (in this case, travel time) in two time periods. This is to assume that the pattern of travel time variation over time remains basically same between these two days.

Assume that for all i, j, $E[w(i)v(j)]=0$, and let $P(t)$ denote the covariance of the estimation error at time interval t, then the filtering procedure is shown as follows:

Step 0: Initialization

Set $t=0$ and let $E[x(0)]=\hat{x}(0)$ and $E\left[(x(0)-\hat{x}(0))^2\right]=P(0)$.

Step 1: Extrapolation

State estimate extrapolation: $\hat{x}(t)_- = \phi(t-1)\hat{x}(t-1)_+$.

Error covariance extrapolation: $P(t)_- = \phi(t-1)P(t-1)_+\phi(t-1)+Q(t-1)$

Step 2: Kalman Gain Calculation

$K(t)=P(t)_-[P(t)_- + R(t)]^{-1}$

Step 3: Update

State estimate update: $\hat{x}(t)_+ = \hat{x}(t)_- + K(t)[z(t)-\hat{x}(t)_-]$.

Error covariance update: $P(t)_+ = [I-K(t)]P(t)_-$

Step 4: Let $t=t+1$ and go back to Step 1 until the preset time period ends.

EXAMPLE

The example used in the study is a segment of the I-80, a major transportation corridor in New Jersey carrying large volumes of long distance, inter-regional and intrastate commercial traffic and commuters. Figure 2 shows the outline of the freeway segment and the abstracted link-node diagram. There are nine links in the segment. Each node associated with an on-ramp as well as the start of the freeway segment (i.e., node 340) is considered as origin, and each node associated with an off-ramp as well as the end of the freeway segment (i.e., node 411) is considered as destination.

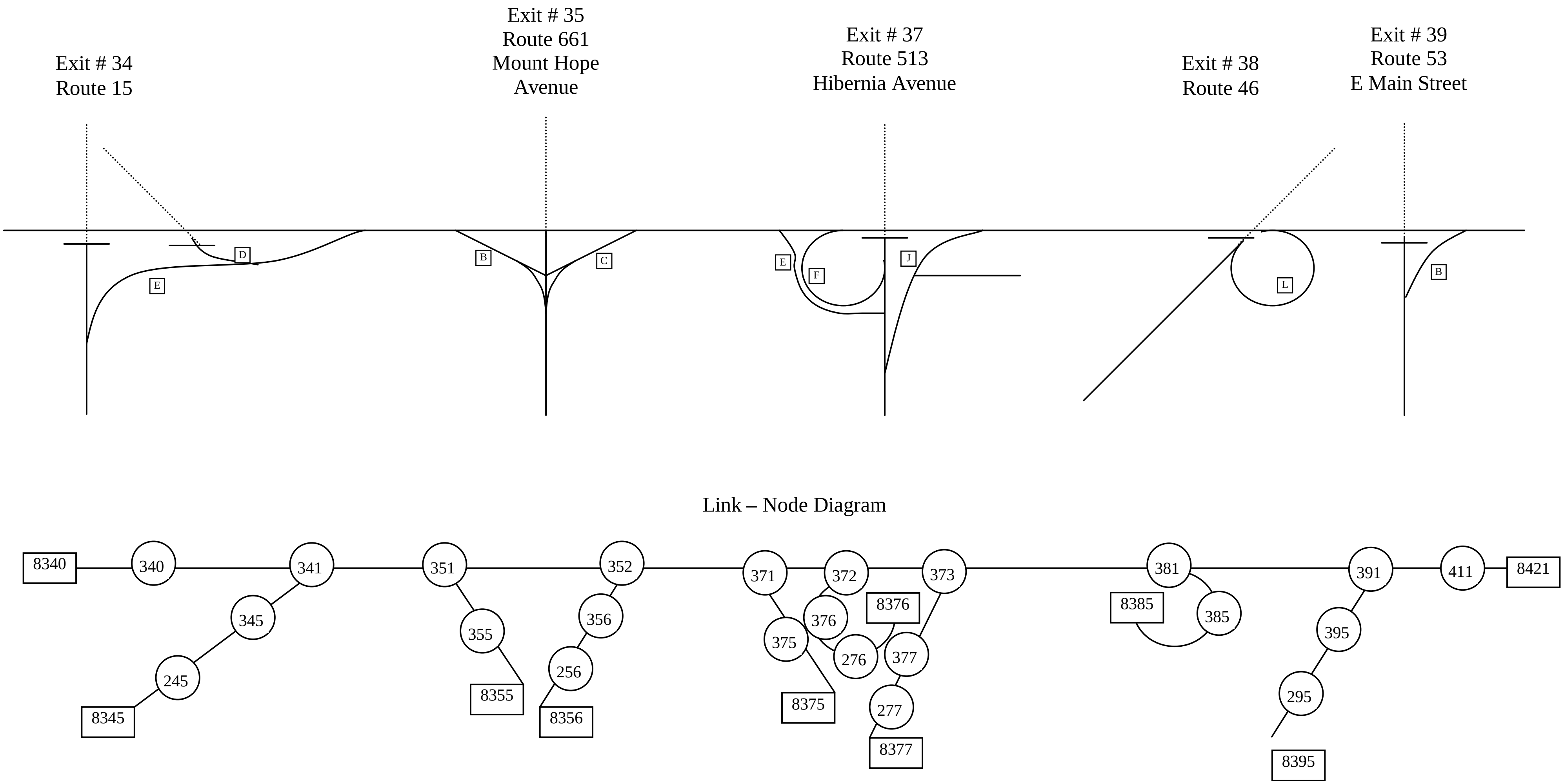

Figure 2 Diagram of I-80 Eastbound Milepost 34-42

In this study, the origins and destinations are projected to the mainline nodes from the on/off-ramp end points. Therefore, the set of origin is {340, 341, 352, 372, 373, 391} and the set of destinations is {351, 371, 381, 411}. Based on a previous study on the transportation need assessment (17), a microscopic simulation model based on CORSIM is established to emulate the traffic condition during a two-hour peak period in the morning. The variable demand level for this two-hour period is shown in Figure 3.

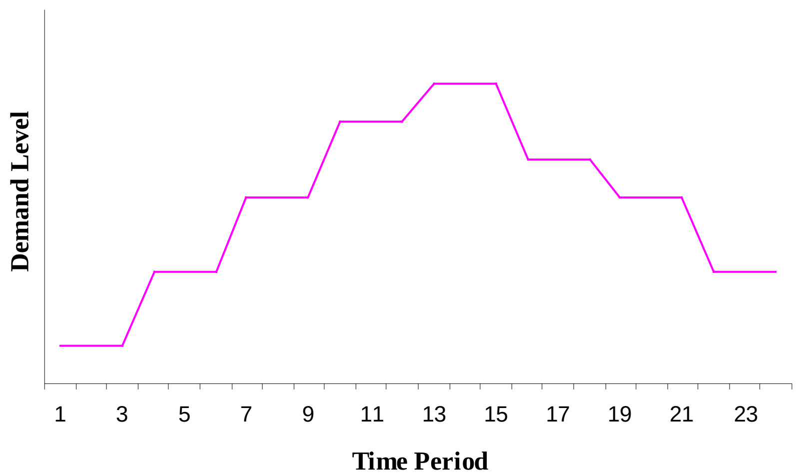

Figure 3 Demand Level within the Two-Hour Time Period

We sample 1% of all vehicles on the network as probe vehicles to reflect the relatively low market penetration of vehicle identification devices. Obtained from simulation output, average travel time of probe vehicles is used as real-time observation in the prediction model. A 5-minute interval is chosen in the example for the short-term travel time prediction. Even though travel time is indeed a continuous variable, for the purpose of prediction, we consider it as a discrete variable with 5min interval.

The freeway segment from node 341 to 411 is chosen as the path on which travel times of probe vehicles are recorded. It consists of eight links with different lengths, as shown in Figure 2. For path-based method, probe vehicle's passing is only recorded at the beginning and the end of the path (i.e., at nodes 341 and 411). Therefore, the time varying movement based travel times on the links with ramps can be handled. For link-based method, the passing is recorded at all nodes in the path (i.e., at nodes 341, 351, 352, 371, 372, 373, 381, 391, and 411) and the path (from node 341 to node 411) travel time is the addition of travel times on all consisting links.

There are two methods to obtain path travel time for vehicles entering the path at certain time period (in this case, 5 minutes) using link-based method. Method (I) is to get simple addition of the travel times on all consisting links in the same time period. Method (II) is to get a "progressive" addition, which only does simple addition for the current time period (until the travel time from the path origin falls into the next time period). Then the addition procedure goes into next time period till the path destination has been reached.

The basic procedure to collect travel time data from probe vehicles is demonstrated below:

Step 1: Conduct microscopic simulation.

Step 2: Generate probe vehicle information by sampling 1% of all vehicles.

Step 3: Set initial time period t.

Step 4:

(a) For path-based method, record travel times on path (341-411) for those probes entering the path at time period t, and get the average probe travel time. Then, go to Step 5.

(b) For link-based method, record travel times on links (341-351), (351-352), …, (391-411) for those probes entering the links, and get the average probe travel time for each link. Then, go to Step 5.

Step 5: If t reaches the preset time period limit T, then go to Step 6; Otherwise, let $t = t + 1$ and go to Step 4.

Step 6:

(a) For path-based method, the average probe travel time is used as the real-time observation of travel time at each time period.

(b) For link-based method, calculate path travel time by adding travel times on all consisting links. This is considered as the real-time observation of travel time at each time period.

Using this real-time reports of probe vehicles from simulation results as the observation of travel time at each time interval, the predicted travel time on links and path can be obtained by following the Kalman filtering procedure introduced earlier.

RESULTS AND ANALYSIS

The predictions of travel times from node 341 to node 411 using the link-based and path-based methods are shown in Figure 4. For comparison purpose, the "true" average travel time of all vehicles during each 5-minute interval is also shown in the figure.

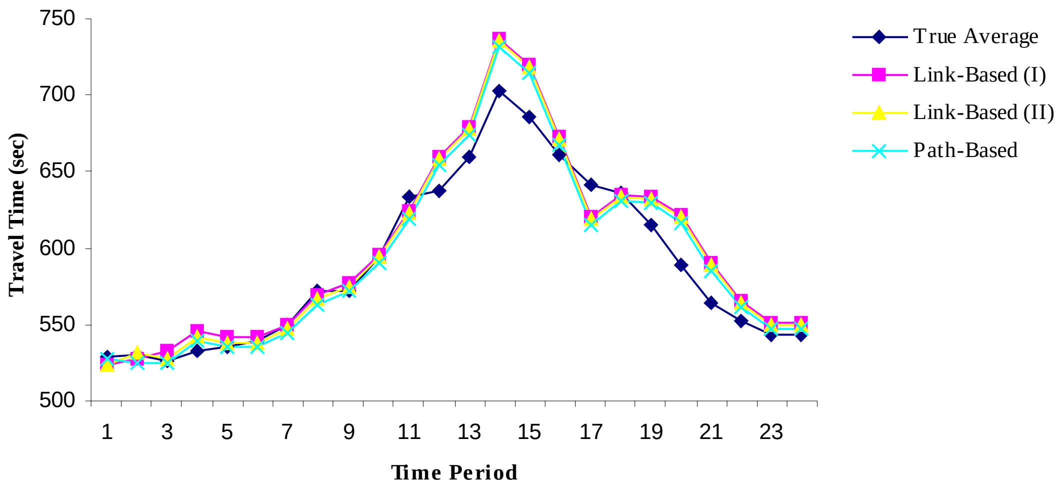

Figure 4 Comparison of Prediction Results

In addition, several prediction error indices, mean absolute relative error (MARE), root relative square error (RRSE), and maximum relative error (MRE) are computed. These indices are defined as:

$$MARE = \frac{1}{N}\sum_t \frac{|x(t) - \hat{x}(t)|}{x(t)}$$

$$RRSE = \sqrt{\frac{1}{\sum_t x(t)} \sum_t \left[\frac{x(t) - \hat{x}(t)}{x(t)}\right]^2 x(t)}$$

$$MRE = \max_t \frac{|x(t) - \hat{x}(t)|}{x(t)}$$

in which N is the number of samples.

The prediction error indices are listed in Table 1. First, between the two link-based prediction methods, method (II) certainly has a better performance than method (I). This is relatively easy to understand – method (II) involves a more realistic measure of link travel time that is "progressive".

Table 1 Prediction Error Indices Comparison

	MARE	RRSE	MRE
Link-Based (I)	0.0208	0.0272	0.0549
Link-Based (II)	0.0192	0.0257	0.0528
Path-Based	0.0173	0.0232	0.0473

One can also see that for all indices, the path-based travel time prediction produces better results compared to the link-based methods. Even though the absolute number of these performance measures are small and look close to each other, we can see that path-based prediction model performs about 19% and 10% better than the link-based method (I) and (II), respectively, based on *MARE* only. Tests on multiple data sets show the similar results. Therefore, it can be concluded that path-based prediction method would produce a better result than the link-based methods. The difference in the prediction performance can be attributed to the variance of the probe reports. Adding link travel time together will certainly propagate the variance of the total travel time of the path. Therefore, with larger variance on travel time estimates, the link-based prediction models are more likely to produce less satisfactory results.

Theoretically, it is expected that the prediction gets more and more close to the "true" value of the state variable (travel time) with increasing number of real-time observations. However, the relative prediction error of either link-based or path-based model does not display such a trend, as observed from Figure 4. Instead, it can be seen that the prediction errors for both cases are relatively larger starting from the 12^{th} time period of the two-hour frame. The reason is two-folded. First, for the purpose of forecasting, travel time on a link or path during a time period is recorded as the difference of exiting and entering time stamps of the vehicle if it enters the link or path within this time period. This could results in a "lag" in the travel time distribution curve, especially for those time periods with longer travel times. Second, Kalman filtering process needs real-time observation at each time period as input to update the estimates, and the observations are obtained from probe vehicle reports. The accuracy of these real-time probe travel times with respect to the "true" average travel time plays a very important role here. As mentioned earlier, 1%

probe vehicles are sampled from the vehicle population in the simulation output. In a previous study of the same roadway system, it was argued that at least 3% probe vehicles are necessary to provide statistically accurate estimate of travel time under a significance level of 0.05. Particularly, for the heavy flow condition in time periods 13 – 15, 12% probe vehicles are needed to ensure accurate estimates (11). Therefore, the travel time estimated provided by only 1% probe vehicles would result in large variation from the “true” value, as displayed in Figure 4.

Considering these factors, similar computation is conducted for the case of 3% probe vehicle for both link-based and path-based prediction methods. The predicted travel time using either method demonstrates a similar trend with that shown in Figure 4. Table 2 shows the prediction error indices for this case. It can be seen that all values of these indices become smaller compared to the corresponding items in Table 1. Path-based prediction method still outperforms link-based methods – it performs 12% and 8% (based on MARE) better than link-based method (I) and (II), respectively.

Table 2 Prediction Error Indices Comparison for the Case of 3% Probe Vehicles

	MARE	RRSE	MRE
Link-Based (I)	0.0194	0.0255	0.0517
Link-Based (II)	0.0187	0.0248	0.0497
Path-Based	0.0171	0.0213	0.0459

Even though there is an improvement of the prediction accuracy, as expected, after increasing probe vehicle percentage from 1% to 3%, the improvement is not that significant – only 2.6% and 1.2% for link-based (II) and path-based prediction methods, respectively. Despite the random factors associated with probe vehicle sampling, we may have an interesting observation that 1% probe vehicles, even though far less than the minimum required number for a statistically accurate estimate, would work almost as good as 3% probe vehicles.

CONCLUSIONS AND FUTURE STUDY

In this study, Kalman filtering technique is used to carry out the dynamic travel time prediction, which is based on real-time reports of probe vehicles. Several conclusions can be drawn. First, it has been proved that the path-based travel time prediction method has a better performance over the link-based prediction method under the normal flow condition. This can be attributable to the fact that, when the variance of system measurement remains the same, adding link travel times may propagate the variance of the path travel time in the link-based method which will increases prediction error.

The use of probe reports as real-time observation results in the fact that the variance of observations in each time period may vary. For a given probe percentage (e.g., 1%), larger variance of travel times reported by probe vehicles are expected when traffic volume approaches capacity, which would results in larger prediction errors. This explains the observation in Figure 4 that for higher demand level (indicated in Figure 3), prediction errors tend to be larger.

Increasing probe vehicle percentage could somewhat improve the prediction accuracy for both link-based and path-based methods. However, this improvement is not significant. In our example, increasing probe vehicle percentage from 1% to 3% only improved the prediction accuracy by less than 3% in terms of MARE. This shows that real-time observations from only 1% probe vehicles, as an input in the Kalman filter, can provide a travel time prediction with similar accuracy to that from 3% probe vehicles. Previous study showed that 3% is the minimum percentage required for a statistically accurate link travel time estimate. However, in real world ITS applications, the percentage of vehicles that are equipped with vehicle identification devices could be much less than 3%. The observation that fewer probe vehicles could provide similar estimates of travel time might shed some light on the implementation of traveler information system without a high market penetration of such devices. Future research is needed on this issue to further explore the relationship between the probe percentage and the prediction error.

The simulation model in the study can handle recurrent traffic (incident-free) condition. All the comparisons and conclusions regarding link-based and path-based prediction methods are also based on this condition. However, link-based method could be more sensitive to incident. Intuitively, when vehicle probes are the only source of traffic data, closely tracking link travel time could facilitate incident detection. Further research under this scenario will be carried out to evaluate the performance of link-based and path-based prediction methods.

ACKNOWLEDGMENT

This study is based upon work supported by the New Jersey Commission on Science and Technology under Grant No. 99-2042-007-20. We would like to express our appreciation to Dr. Louis Pignataro (NJIT), Dr. David Bernstein (James Madison University), Dr. Alan Kornhauser (Princeton University), Dr. John Tavantzis (NJIT), and Dr. Kyriacos Mouskos (NJIT) for their valuable guidance and suggestions on the study.

We would also like to extend our thanks to Dr. Lazar Spasovic (NJIT) for his support on the further modification of this work.

REFERENCES

1. Oda, T. An Algorithm for Prediction of Travel Time Using Vehicle Sensor Data. *Proceedings of the IEE 3rd International Conference on Road Traffic Control*, London, 1990, pp.40-44.

2. Al-Deek, H., M. D'Angelo and M. Wang. Travel Time Prediction with Non-Linear Time Series. *Proceedings of the ASCE 1998 5th International Conference on Applications of Advanced Technologies in Transportation*, Newport Beach, CA, 1998, pp.317-324.

3. Anderson, J., M. Bell, T. Sayers, F. Busch, and G. Heymann. The Short-Term Prediction of Link Travel Time in Signal Controlled Road Networks. *Proceedings of the IFAC/IFORS 7th Symposium on Transportation Systems: Theory and Application of Advanced Technology*, Tianjin, China, 1994, pp.621-626.

4. Park, D., L. Rilett, and G. Han. Forecasting Multiple-Period Freeway Link Travel Times Using Neural Networks with Expanded Input Nodes. *Proceedings of the ASCE 1998 5th International Conference on Applications of Advanced Technologies in Transportation*, Newport Beach, CA, 1998, pp.325-332.

5. Rilett, L. and D. Park. Direct Forecasting of Freeway Corridor Travel Times Using Spectral Basis Neural Networks. *Presented at the 78th TRB Annual Meeting (CD-ROM)*, Washington, DC, 1999.

6. Roden, D. Forecasting Travel Time. In *Transportation Research Record 1518*, TRB, National Research Council, Washington, DC, 1996, pp.7-12.

7. D'Angelo, M., H. Al-Deek, and M. Wang. Travel Time Prediction for Freeway Corridors. *Presented at the 78th TRB Annual Meeting (CD-ROM)*, Washington, DC, 1999.

8. Pant, P., M. Polycarpou, P. Sankaranarayanan, B. Li, X. Hu, and A. Hossain. Travel Time Prediction System (TIPS) for Freeway Work Zones. *ASCE Proceedings of the ICTTS'98 Conference on Traffic and Transportation Studies*, Beijing, China, 1998, pp.20-29.

9. Sen, A., N. Liu, P. Thakuriah, and J.Li. Short-Term Forecasting of Link Travel Times: A Preliminary Proposal. *ADANCE Working Paper Series #7*, 1991.

10. Srinivasan, K. and P. Jovanis. Determination of Number of Probe Vehicles Required for Reliable Travel Time Measurement in Urban Network. In *Transportation Research Record 1537*, TRB, National Research Council, Washington, D.C., 1996, pp. 15-22.

11. Chen, M. and S. Chien. Determining the Number of Probe Vehicles for Freeway Travel Time Estimation Using Microscopic Simulation. Accepted for Publication in *Transportation Research Record*. 2000.

12. Sen, A., P. Thakuriah, X. Zhu, and A. Karr. Frequency of Probe Reports and Variance of Travel Time Estimates. *ASCE Journal of Transportation Engineering*. Vol.123, No.4, 1997, pp.290-297.

13. Kalman, R. A New Approach to Linear Filtering and Prediction Problems. *Journal of Basic Engineering*, 82D (1), 1960, pp.35-45.

14. Okutani, I. and Y. Stephanedes. Dynamic Prediction of Traffic Volume through Kalman Filtering Theory. *Transportation Research, Part B*, Vol.18B, No.1, 1984, pp.1-11.

15. Okutani, I. The Kalman Filtering Approaches in Some Transportation and Traffic Problems. In *Transportation and Traffic Theory*, N. Gartner and N. Wilson (Ed.), Elsevier Science Publishing Co., Inc., 1987.

16. Stephanedes, Y. and E. Kwon. Adaptive Demand-Diversion Prediction for Integrated Control of Freeway Corridors. *Transportation Research, Part C*, Vol.1c, No.1, 1993, pp.23-42.

17. Garmen Associates. *Interstate 80 Corridor Transportation Needs Assessment*. Final Report, Prepared for New Jersey Department of Transportation, 1991.